A Framework to Select Edge Detection Method using Multi-criteria Decision Making

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Abstract—In the fields of computer vision and image processing, edge detection refers to the identification and localization of significant changes in a digital image. This article presents a survey of widely-used edge detection techniques including linear approaches, morphological operations, multi-resolution analysis, and machine learning methods. Since there exists no single method that is applicable in all situations, different methods are deployed for different applications. A hierarchical framework based on multiple criteria has been proposed here that can facilitate the process of selecting the most appropriate edge detection method in a given scenario. Use of the proposed framework has been explained through an example of medical images. Finally, possible areas for further exploration have been highlighted.

Index Terms—edge detection, boundary, filters.

I. INTRODUCTION

In machine vision and image processing, edge detection is a technique to identify points on which the image brightness changes significantly. The identification of such points and curves in an image facilitates the subsequent tasks of interpreting information available in the image. The primary objective of an edge detection method is to highlight interesting phenomena in a given image, and also in the given scenario. This twofold objective impose great deal of constraints in practical problems and therefore no method is considered to be optimal in all situations.

Edge detection significantly reduces the amount of data by filtering out unwanted information in an image. The reduced information is then processed according to the need of application, for example, to detect, identify and track objects of interest. Edge detection has been extensively used in the pre-processing phase of image segmentation - an important step in many vision-based applications. For example, edge detection can be used to detect number of vehicles on a road to adjust the timings of traffic signals [1]. Another application of edge detection is the counting of blood cells from microscopic images of patient's blood [2]. This helps in detecting diseases like anaemia, leukaemia etc. Moreover, edge detection is also used in face detection and recognition, road side detection for autonomous vehicles, and extracting maps from aerial photographs.

There exist various challenges in detecting edges including, for example, the problems of false-edge detection [3], [4],

robustness against noise, and capturing low-contrast boundaries [5]. This paper presents a comparison between various edge detectors to identify which edge detector performs better in a given situation. As a consequence, a framework has been proposed, based on the multi-criteria decision making (MCDM) methods, in order to select the most suitable edge detection technique for a given application.

Considering the diversity of the edge-detection problems, no method can be declared the most suitable in all situations. Hence, a performance comparison matrix has been proposed in this article that may assist decision maker in prioritizing these methods for a given problem. For example, evolutionary computation based methods may be preferred over classical gradient-based methods in case of having noisy images. Next, we review the widely-used techniques for edge detection.

II. BACKGROUND

An image is a function that represents intensity in terms of spatial coordinates in two dimensions. Images of more than two dimensions are also possible where third dimension usually represents the depth of captured objects and the fourth dimension is usually related to time. The spatial coordinates can also be represented in only one dimension, for example, line scans are widely used in embedded systems for industrial inspection. However, the most common form of representing an image is in two dimensions.

In raster images, edges consist of pixels where the brightness function changes abruptly, and can be seen as a local discontinuity in the image intensity. Discontinuities in the image intensity can be classified into four types i.e. step, line, roof and ramp edges. In a step edge, the image intensity suddenly changes from one value to another one. Line edges are those edges where the image intensity abruptly changes value but then returns to the starting value within a short distance. Since high frequency components (or smoothening) are resisted by most sensing devices, sharp discontinuities rarely exist in real signals. Therefore, in practice, step edges become ramp edges and line edges become roof edges. In other words, the intensity changes are not immediate but occur over a finite distance and time.

An image can be converted into edge image using various techniques that transform the image without performing any

changes in physical quantities, for example, without changing the image dimensions.

A. Classical or Gradient-based Detectors

Since edge represents change in the brightness level, calculating the gradient of the image turns out to be the most primitive form of linear edge detection. Roberts [6] proposed a slight modification to the basic gradient operation by detecting edges in the directions of $\frac{\pi}{4}$ and $-\frac{\pi}{4}$ instead of using horizontal and vertical axes. These operators perform a simple set of measurements on an image and highlight regions of high spatial frequency which often relate to edges. Prewitt [7] and Sobel [8] then proposed to calculate edges using slight modifications in the template functions. The gradient operators only detect those edges having certain orientations, and do not perform well when the edges are blurred and noisy [9].

Marr and Hildreth [10] revealed the fact that the variation of image intensity (edge) appears at different levels. This indicated the demand to use smoothening filters at different scales because a single filter cannot produce optimal results at all levels. The two operations of Gaussian and Laplacian can be combined to produce a single template, known as Laplacian of Gaussian (LoG). The LoG operator is the second derivative of the smoothed version of image.

A drawback of using LoG operator is the introduction of bias in the localization of edges with an asymmetric profile by zero-crossing points. To deal with this problem, Canny [11] proposed to use the first-derivative of Gaussian operator for detecting step edges in the presence of additive Gaussian noise. His edge detection method turns out to be an improvisation of the LoG filter [10].

B. Multi-resolution Techniques

Recall the fact that the variation of image intensity (edge) appears at different levels; therefore, multiple scales should be employed to describe the edge structures. In this type of techniques, edges are measured at different level of resolution [12] that are synthesized to form an edge map.

A wavelet, in its simplest form, is a time-bounded oscillation that increases in magnitude and then decreases back to zero. Like sinusoids in Fourier transforms, a variety of wavelets can be used to extract information from the given signal. Mallat [13] was amongst the first ones to discuss its applications in the field of image processing and showed that wavelet transforms provide an insight on the statistical properties of images. Mallat and Zhong [14] showed that the local maxima in a wavelet transform of an image can be used to detect and locate edges in that image. Since then, several wavelet-based edge detection operators have been proposed to date (see [15], [16], [17] for example).

C. Morphological Approaches

Morphology is a graph-theoretic approach commonly used in image processing. The common morphological operations include dilation, erosion, opening and closing of binary or grayscale images [18]. A simplest technique with the morphological approach is to take the difference of an image

with its own eroded version. For example, Lee et al. [19] proposed morphologic edge-detection with the help of a small rod-shaped structuring element. Similarly, Song and Neuvo [20] proposed an alternating sequential filter i.e. an iterative process of opening and closing operations wherein the size of structuring element is increased after each iteration. Morphological approaches have remained under investigation quite recently (See for instance, [21], [22], and [23]).

D. Statistical Approaches

Various edge detection techniques have been proposed using statistical approaches, for example, a bidimensional recursive filtering scheme using statistical modeling of the image [24], and to use statistical edge detection using model-based detection [25]. Konishi et al. [26] also proposed an edge detection method using probability distributions of edge and non-edge regions. Multiple edge cues, along with chrominance and multiple-scale, are linked by using their joint distributions.

a) *Support Vector Machine*: Support vector machine (SVM) is a statistical approach for classification (and regression) problems. In [27], an algorithm has been proposed that estimates the image intensity derivatives produced by least square SVMs. Zheng et al. compared their hybrid approach to the Canny and Sobel detectors and concluded that their method can be optimized with respect to many parameters. However, it can be argued that setting too many parameters may lead to an information overload.

Statistical approaches have led this field of image processing to a new era of computing i.e. computational intelligence based methods. Next, we discuss methods under this category.

E. Methods based on Computational Intelligence

Traditional computational approaches usually fail to model complex real-world problems and become ineffective or infeasible to handle issues like uncertainty, noise and dynamically changing environment/parameters. In recent decades, a set of nature-inspired computational methodologies have emerged that are able to perform much better than the traditional approaches. These techniques enable the computer systems to perform reasoning and making decisions in collaboration with (and sometimes, on behalf of) humans.

1) *Fuzzy Logic*: Lu et al. [28] were amongst the first ones to propose the use of fuzzy logic for the purpose of edge-detection. They proposed an edge detection and enhancement algorithm based on fuzzy system for recovering missing edges and discarding false edges caused by noise. Becerikli and Karan [29] proposed the detection of edges based on simple if-then rules using FL. They asserted that fuzzy rules based algorithm is more flexible in handling the thickness of edges. Chaira and Ray [30] proposed a fuzzy distance measure for edge detection, based on intuitionistic fuzzy sets proposed in [31]. The proposed method was shown to have performed better than other (classical) methods by removing the unwanted edges, leaving only the dominant edges for further processing.

2) *Neural Networks*: Neural network (NN) symbolize a computational mechanism based on a simplified mathematical model of the perceptrons (neurons) and signals that they process. Paik and Katsaggelos [32] used this technique with the help of multi-state adaptive linear neurons (ADALINES). The proposed algorithm suppresses noise and is not dependant on the orientation of edges (*rotation-invariant*). Recently, the concept of NNs has been hybridized with the wavelet theory (as WNN); and a novel, multi-resolution NN-based algorithm has been proposed for edge detection [33]. The proposed algorithm combines the good localization characteristics of wavelets with the adaptive learning properties of NNs.

3) *Evolutionary Computation*: Evolutionary computation methods are a set of techniques to solve problems using the concept of evolution. To detect edges using Genetic Algorithm (GA), Bhandarkar et al. [34] presented a cost minimization approach by applying several combinations of meta-level operators on multiple images. They compared the performance of the GA with local search and imitated annealing approaches, and concluded that GA performs excellently in terms of robustness to noise, rate of convergence and quality of the final edge image.

Particle Swarm Optimization (PSO) is one of the population-based approach proposed by Kennedy and Eberhart [35]. The advantages of using PSO technique for edge detection includes ease of its implementation, limited operators, a bounded memory for each particle to save its previous state, and high speed of convergence [36].

Another popular method using swarm intelligence is Ant Colony Optimization (ACO) technique where a number of artificial ants build solutions to an optimization problem by exchanging information on their quality. In edge detection using ACO-based technique, artificial ants are distributed over an image and moved based on the local variation of the image's intensity values [37], [38].

F. Trends in Edge Detection

Since there exists no single method that outperforms all other methods in all situations, a variety of techniques have been recently proposed, for example, fuzzy derivative combined with ACO [39]; applying constraint optimization using PSO [40], [41]; and Otsu method combined with rough set theory for approximating edges [42].

A concept of directionlet transformation [43] has also been recently proposed to detect edges in an image. This transformation has been shown to have better results when detecting geometrical feature in the image.

Another interesting idea has been introduced in [44] wherein the concept of gravitational force has been remodelled for detecting edges. Image pixels are considered to be celestial bodies that attract each other by the gravitational force, and the net gravitational force on each pixel defines its edge intensity.

III. A FRAMEWORK TO SELECT APPROPRIATE METHOD

When comparing the available edge-detection methods, there exists no single method that outperforms the other methods for all types of images. The problem of choosing the most

suitable method depends on multiple criteria. These criteria are not always supposed to be the *tangible* ones. For example, in edge detection, processing time, memory consumption and rotation invariance can be considered tangible criteria. On the other hand, some intangible criteria like robustness against noise, false edge detection and sensitivity to illumination may depend on the specific task that needs to be performed.

In the field of decision making, there exists several techniques to facilitate decision makers in prioritizing the available options. The widely used methods are *Simple Multi-Attribute Ranking Theory* (SMART) [45], *Technique for Order Preference by Similarity to Ideal Solution* (TOPSIS) [46], *ELimination Et Choix Traduisant la REalité* (ELECTRE) [47], *Preference Ranking Organization Method for Enrichment Evaluation* (PROMETHEE) methods [48] and *Analytic Hierarchy Process* (AHP) [49]. As one would expect, different techniques may yield different results for the same problem.

Wallenius et al. [50] compared these methods and highlighted the method of AHP as the most active and growing area of research. The AHP method is based on pairwise comparisons to assess relative importance of *criteria* and *options*. The main benefit of using this approach is to convert both objective and subjective judgments into relative weights of importance. Here, we propose to use AHP for selecting appropriate edge-detection method for any given application.

A. Hierarchy of Criteria for Detecting Edges

In order to detect edges, each algorithm can be assessed on the basis of three primary aspects viz. available resources, robustness required and the method's ability to adapt to different conditions. Resources can further be divided into three main sub-criteria including memory usage, computational cost, and the ability to parallelize in order to gain maximum benefit from multiprocessor architectures. Similarly, the aspect of adaptability can be categorized into orientation and background dynamicity. An algorithm should be able to detect edges from a set of similar images captured with different angles (orientation) of the same object. Background dynamicity implies that slight variations in the background image should not affect the edge detection process for foreground objects. The third and last aspect of robustness can be divided into the sub-categories of robustness against noise, blur and other possible distortions. Noise can further be sub-divided into different types e.g. Gaussian distributed, Salt-and-pepper, and uniformly distributed noise etc. Blur can also be categorized as out-of-focus blur or the motion blur. In addition to these, edge detection algorithms can be assessed based on their performance in the presence of bad illumination, discontinuities, and occlusion. In any case, no method should detect false edges.

In order to select the most suitable edge detection algorithm for a given application, a hierarchy of all these criteria can be constructed as shown in Fig. 1. Although it can be argued that more criteria needs to be added or some criteria to be removed, the construction of hierarchy itself turns out to be a useful

Figure 1: Hierarchy of Criteria for Selecting An Edge Detection Method

tool for structured analysis of the available edge detection techniques.

The *pros* and *cons* of these edge detection methods can possibly be converted into a linguistic scale, having 'poor', 'average', 'good', and 'excellent' as possible values for each criterion listed in Fig. 1. An example of such grading is given in Table I, where each row represents edge detection method and columns for the criteria taken from Fig. 1. It is to be clarified here that this table has been filled as an example, and some of the assigned scores are open for argument. The emphasis here is not the validity of these scores, rather to convey the message that the problem of selecting an edge detection technique can be transformed into an MCDM problem.

IV. EDGE-BASED SEGMENTATION FOR CT IMAGES: AN EXAMPLE

Medical imaging is a process of acquiring and/or creating images of human body for clinical purposes. Considering the large amount of information generated in the form of medical images, automated processing is becoming a necessity to effectively extract useful knowledge from it. For example, computed tomography (CT) scanners generate volume of images during cardiac exams that must be processed in order to extract useful knowledge [51].

In such situations, simple methods like global thresholding or region growing generally fail to automatically segment an image due to several reasons including noise, blur, and poor resolution [52]. The algorithms for medical images are usually customized for detecting edges in a certain modality, usually for better performance [53]. However, they cannot be generalized to other modalities or other anatomic structures.

Imagine a situation where CT images need to be processed automatically without human intervention during the process. In order to segment each image, edge-detection is required to clearly mark the boundaries of objects that are present in the given image. Although there exists other techniques for segmentation, we consider edge-based segmentation in order to explain here the proposed framework.

The hierarchy of criteria given in Fig. 1 needs to be evaluated in the given scenario. Let us walk through the hierarchy;

starting from the top three criteria of 'resources', 'robustness' and 'adaptability'. For medical diagnosis, the robustness of results is much more important than computational resources. In other words, if the results are not robust, the laboratory must arrange for better computational facility, otherwise the results may take unacceptable amount of processing time.

CT images are captured in a controlled environment where subject is asked to restrict his/her movements. Moreover, the background and lighting conditions are also well-maintained and therefore images are generally of similar sizes, shapes and backgrounds. In such a scenario, adaptability may not be an important criterion for selecting the edge-detection method. However, the criterion of adaptability should be preferred over computational resources for medical imaging. This leads us to the following order of preference:-

Robustness → Adaptability → Computational resources

Similarly, the sub-criteria of noise, blur, and proneness need to be compared under the category of robustness. In the case of CT scans, removing noise should be considered of high importance. Although image blur badly affects the results, it is highly unlikely to have blurred images during CT scan, and if so, subjects can be re-scanned. Therefore, the noise criterion is more important than handling blurred images. The sub-criterion of proneness is more important than others, due to the fact that false or discontinued edges may end up in poor segmentation of CT images. Therefore, proneness will have preference over handling noise, and noise will have preference over handling blur i.e. Proneness → Noise → Blur. Similarly, all the other criteria must be evaluated in order to rank the available edge-detection methods for given scenario. Acquiring all the judgments for this problem is considered to be an area of further investigation.

Refer to the columns under 'proneness' in Table I, the GA method remains 'excellent' in all the three criteria of handling 'variations in illumination', 'false edges' and 'edge discontinuities'. Therefore, according to this table, GA should be used to detect edges in CT scans. It should be noted that the hierarchy and table of judgments given above should not be considered authentic or final. They are provided here only to explain the use of MCDM in choosing the most appropriate

Method	Resources			Robustness								Adaptability	
	Computation	Memory	Parallelization	Noise			Blur		Proneness			Orientation	Background
				Gaussian	Uniform	Salt & Pepper	Focal	Motion	Illumination	False Edges	Discontinuities		
Roberts	Good	Excellent	Excellent	Poor	Poor	Poor	Poor	Poor	Poor	Good	Poor	Poor	Poor
Prewitt	Good	Excellent	Excellent	Poor	Poor	Poor	Poor	Poor	Poor	Good	Poor	Poor	Poor
Sobel	Good	Excellent	Excellent	Poor	Poor	Poor	Poor	Poor	Poor	Good	Poor	Poor	Poor
Marr	Good	Excellent	Excellent	Excellent	Excellent	Average	Good	Average	Average	Poor	Good	Poor	Poor
Canny	Average	Excellent	Excellent	Excellent	Excellent	Average	Excellent	Average	Average	Excellent	Excellent	Excellent	Poor
Wavelet	Good	Average	Good	Excellent	Excellent	Excellent	Excellent	Excellent	Good	Excellent	Excellent	Excellent	Good
Morphology	Poor	Excellent	Excellent	Average	Average	Good	Excellent	Poor	Average	Excellent	Good	Good	Average
Statistical	Excellent	Good	Average	Good	Good	Good	Good	Average	Good	Good	Excellent	Good	Good
SVM	Excellent	Average	Average	Excellent	Excellent	Excellent	Good	Good	Excellent	Excellent	Good	Excellent	Excellent
Fuzzy	Excellent	Average	Good	Excellent	Excellent	Good	Excellent	Average	Good	Excellent	Excellent	Good	Good
NN	Good	Poor	Average	Excellent	Excellent	Good	Good	Excellent	Excellent	Good	Good	Excellent	Excellent
GA	Poor	Poor	Good	Excellent	Excellent	Excellent	Excellent	Excellent	Excellent	Excellent	Excellent	Good	Excellent
PSO	Good	Average	Good	Excellent	Excellent	Good	Excellent	Excellent	Excellent	Good	Good	Excellent	Excellent
ACO	Good	Average	Good	Excellent	Excellent	Good	Excellent	Excellent	Excellent	Good	Good	Excellent	Excellent

Table I: Comparison table for edge detection methods

edge-detection method.

So far, the order of preferences has been acquired without considering the cardinality of preferences. The next question is how to gauge these preferences cardinally e.g. how much should robustness be preferred over adaptability? The problem is complex due to the fact that the two criteria have different units of measurement. This problem is sometimes referred to as adding apples to oranges [54]. In the field of psychometry, however, different scales have been proposed, including Bradley-Terry model [55] and Thurstonian model [56]. The authors propose to collect data through surveys using one of these models where experts in medical image processing will be asked to compare these criteria, and final ranking will be drawn from their results combined.

V. CONCLUSION

A survey of widely-used edge detection techniques have been performed and it has been concluded that there exists no single method that is applicable in all situations. Some of the methods perform faster but are noise-sensitive, while others handle noise at the expense of memory consumption and computation time. In practice, various edge detection methods are deployed for different applications. Therefore, the problem is considered to be an MCDM problem where several criteria need to be evaluated. A hierarchical framework has been proposed that can be used to select the most appropriate edge detection method, for a given scenario. The framework has been explained through an example of finding edges in the CT scans.

The article concludes with a number of unanswered questions and future work for the proposed framework. 1) The criteria listed in listed in Fig. 1 are not exhaustive and need to be revised. 2) The pairwise comparison analysis of criteria should be refined by conducting surveys and taking opinion from image processing experts. Since the analysis is application-

specific, the framework may have different values for different applications. 3) How can we rank the available methods in case of incomplete or inaccurate information? 4) The survey of edge detection methods have considered greyscale images and can further include methods based on coloured and/or stereo images. 5) The proposed framework can be developed as a decision support system for image processing community in order for them to select algorithms in a structured way.

REFERENCES

- [1] Y.-C. Chung, J.-M. Wang, and S.-W. Chen, "A vision-based traffic light detection system at intersections," *Journal of Taiwan Normal University: Mathematics, Science and Technology*, vol. 47, no. 1, pp. 67–86, 2002.
- [2] M. Maitra, R. K. Gupta, and M. Mukherjee, "Detection and counting of red blood cells in blood cell images using hough transform," *International Journal of Computer Applications*, vol. 53, no. 16, pp. 13–17, 2012.
- [3] S. Venkatesh and L. J. Kitchen, "Edge evaluation using necessary components," *CVGIP: Graphical Models and Image Processing*, vol. 54, pp. 23–30, 1992.
- [4] C. Lopez-Molina, B. D. Baets, and H. Bustince, "Quantitative error measures for edge detection," *Pattern Recognition*, vol. 46, no. 4, pp. 1125–1139, 2013.
- [5] L. S. Davis, "A survey of edge detection techniques," *Computer Graphics and Image Processing*, vol. 4, pp. 248–270, 1975.
- [6] L. G. Roberts, *Optical and Electro-Optical Information Processing*. MIT Press, 1965, vol. 14, ch. Machine Perception in 3-Dimensional Solids, pp. 159–197.
- [7] J. M. S. Prewitt, B. Lipkin, and A. Rosenfeld, "Object enhancement and extraction," *Picture Processing and Psychopictorics*, pp. 75–149, 1970.
- [8] Sobel, "Sobel operator," pp. 1–5, 1970.
- [9] M. Basu, "Gaussian-based edge-detection methods - a survey," *IEEE Transactions on Systems, Man, and Cybernetics - Part C: Applications and Reviews*, vol. 32, no. 3, pp. 252–260, 2002.
- [10] D. C. Marr and E. Hildreth, "Theory of edge detection," *Proceedings of the Royal Society B: Biological Sciences*, vol. 207, no. 1167, pp. 187–217, 1980.
- [11] J. Canny, "A computational approach to edge detection," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-8, no. 6, pp. 679–698, nov. 1986.
- [12] A. Rosenfeld, *Multiresolution Image Processing and Analysis*. Springer-Verlag, Berlin, Germany, 1984.

- [13] S. G. Mallat, "A theory for multiresolution signal decomposition: The wavelet representation," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 11, no. 7, pp. 674–693, 1989.
- [14] S. G. Mallat and S. Zhong, "Characterization of signals from multiscale edges," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 7, pp. 710–732, 1992.
- [15] J.-W. Hsieh, M.-T. Ko, H.-Y. M. Liao, and K.-C. Fan, "A new wavelet-based edge detector via constrained optimization," *Image and Vision Computing*, vol. 15, no. 7, pp. 511–527, 1997.
- [16] M.-Y. Shih and D.-C. Tseng, "A wavelet-based multiresolution edge detection and tracking," *Image and Vision Computing*, vol. 23, no. 4, pp. 441 – 451, 2005.
- [17] G. K. Srivastava, R. Verma, and R. Mahrishi, "A novel wavelet edge detection algorithm for noisy images," in *International Conference on Ultra Modern Telecommunications & Workshops, ICUMT*, 2009.
- [18] J. Serra, *Introduction to mathematical morphology*. Academic Press, New York, 1982.
- [19] J. Lee, R. Haralick, and L. Shapiro, "Morphologic edge detection," *IEEE Journal of Robotics and Automation*, vol. 3, pp. 142 – 156, 1987.
- [20] X. Song and Y. Neuvo, "Robust edge detector based on morphological filters," *Pattern Recognition Letters*, vol. 14, no. 11, p. 889–894, 1993.
- [21] Z. Li, Y. Yang, and W. Jiang, "Multi-scale morphologic tracking approach for edge detection," in *Fourth International Conference on Image and Graphics, ICIG*, 2007, pp. 358–362.
- [22] X. Bai and F. Zhou, "Edge detection based on mathematical morphology and iterative thresholding," in *Computational Intelligence and Security, Springer-Verlag Berlin*, vol. 2, 2007, pp. 953–962.
- [23] J. Jiang, C. Chuang, and Y. Lu, "Mathematical-morphology-based edge detectors for detection of thin edges in low-contrast regions," *IET Image Processing*, vol. 1, pp. 269–277, 2007.
- [24] J. Modestino and R. Fries, "Edge detection in noisy images using recursive digital filtering," *Computer Graphics and Image Processing*, vol. 6, pp. 409–433, 1977.
- [25] A. Kundu and S. Mitra, "A new algorithm for image edge extraction using a statistical classifier approach," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. PAMI-9, no. 4, pp. 569–577, 1987.
- [26] S. Konishi, A. L. Yuille, J. M. Coughlan, and S. C. Zhu, "Statistical edge detection: Learning and evaluating edge cues," *IEEE Transactions On Pattern Analysis And Machine Intelligence*, vol. 25, no. 1, pp. 57–74, 2003.
- [27] S. Zheng, J. Liu, and J. W. Tian, "A new efficient svm-based edge detection method," *Pattern Recognition Letters*, vol. 25, no. 10, pp. 1143 – 1154, 2004.
- [28] S. Lu, Z. Wang, and J. Shen, "Neuro-fuzzy synergism to the intelligent system for edge detection and enhancement," *Pattern Recognition*, vol. 36, no. 10, pp. 2395–2409, 2003.
- [29] Y. Becerikli and T. M. Karan, "A new fuzzy approach for edge detection," in *Computational Intelligence and Bio inspired Systems*, vol. 3512, 2005, pp. 943–951.
- [30] T. Chaira and A. Ray, "A new measure using intuitionistic fuzzy set theory and its application to edge detection," *Applied Soft Computing*, vol. 8, no. 2, pp. 919–927, 2008.
- [31] K. Atanassov, "Intuitionistic fuzzy set," *Fuzzy Sets Systems*, pp. 87–97, 1986.
- [32] J. Paik and A. Katsaggelos, "Edge detection using a neural network," in *International Conference on Acoustics, Speech, and Signal Processing, ICASSP-90*, vol. 4, 1990, pp. 2145–2148.
- [33] N. Cai, "A wavelet neural network for edge detection," in *Congress on Image and Signal Processing, IEEE*, 2008.
- [34] S. M. Bhandarkar, Y. Zhang, and W. D. Potter, "An edge detection technique using genetic algorithm-based optimization," *Pattern Recognition*, vol. 27, no. 9, pp. 1159–1180, 1994.
- [35] J. Kennedy and R. Eberhart, "Particle swarm optimization," in *IEEE International Conference on Neural Networks*, vol. 4, 1995.
- [36] M. R. A. Rashidi and M. E. El-Hawary, "A survey of particle swarm optimization applications in electric power systems," *IEEE Transactions on Evolutionary Computation*, vol. 13, pp. 913–918, 2009.
- [37] J. Tian, W. Yu, and S. Xie, "An ant colony optimization algorithm for image edge detection," in *IEEE Congress on Evolutionary Computation*, 2008.
- [38] X. Zhuang, G. Yang, and H. Zhu, "A model of image feature extraction inspired by ant swarm system," in *4th International Conference on Natural Computation*, 2008.
- [39] O. P. Verma, M. Hanmandlu, and A. K. Sultania, "A novel fuzzy ant system for edge detection," *IEEE/ACIS 9th International Conference on Computer and Information Science*, pp. 228–233, 2010.
- [40] S. A. Etemad and T. White, "An ant-inspired algorithm for detection of image edge features," *Applied Soft Computing*, vol. 11, no. 8, pp. 4883 – 4893, 2011.
- [41] M. Setayesh, M. Zhang, and M. Johnston, "Edge detection using constrained discrete particle swarm optimisation in noisy images," in *IEEE Congress on Evolutionary Computation (CEC)*, 2011, pp. 246–253.
- [42] J. Zhang and L. Wang, "Image edge detection based on OTSU and rough set theory," in *International Conference on Computer Science and Service System (CSSS)*, 2011, pp. 1318–1322.
- [43] J. Bai and H. Zhou, "Edge detection approach based on directionlet transform," in *Multimedia Technology (ICMT), 2011 International Conference on*, 2011, pp. 3512 –3515.
- [44] G. Sun and Q. Liu, "A new edge detection for multispectral images," in *19th International Conference on Geoinformatics*, 2011, pp. 1–4.
- [45] R. Keeney and H. Raiffa, *Decisions with Multiple Objectives: Preferences and Value Trade-Offs*. Cambridge University Press, 1993.
- [46] C.-L. Hwang and K. P. Yoon, *Multiple attribute decision making: Methods and applications: A state-of-the-art survey*. Berlin: Springer-Verlag, 1981.
- [47] B. Roy, "Paradigms and challenges," in *Multiple Criteria Decision Analysis: State of the Art Surveys*, J. Figueira, S. Greco, and M. Ehrgott, Eds. Springer, 2005, pp. 4–24.
- [48] J. Brans and B. Mareschal, "PROMETHEE methods," in *Multiple Criteria Decision Analysis: State of the Art Surveys*, J. Figueira, S. Greco, and M. Ehrgott, Eds. Springer, 2005, pp. 163–196.
- [49] T. Saaty, "Relative measurement and its generalization in decision making. why pairwise comparisons are central in mathematics for the measurement of intangible factors - the analytic Hierarchy/Network process," *Real Academia de Ciencias, Espana*, vol. 102, no. 2, pp. 251–318, 2008.
- [50] J. Wallenius, J. S. Dyer, P. C. Fishburn, R. E. Steuer, S. Zionts, and K. Deb, "Multiple criteria decision making, multiattribute utility theory: Recent accomplishments and what lies ahead," *Management Science*, vol. 54, no. 7, pp. 1336–1349, 2008.
- [51] O. Ecabert, J. Peters, H. Schramm, C. Lorenz, J. von Berg, M. J. Walker, M. Vembar, M. E. Olszewski, K. Subramanyan, G. Lavi, and J. Weese, "Automatic model-based segmentation of the heart in ct images," *IEEE Transactions on Medical Imaging*, vol. 27, 2008.
- [52] M. Sonka and J. M. Fitzpatrick, *Handbook of Medical Imaging*. Eds. Bellingham, WA: SPIE Press, 2000, vol. 2.
- [53] M. Gudmundsson, E. El-Kwae, and M. Kabuka, "Edge detection in medical images using a genetic algorithm," *IEEE Transactions on Medical Imaging*, vol. 17, no. 3, pp. 469 –474, 1998.
- [54] A. Ishizaka, D. Balkenborg, and T. Kaplan, "Influence of aggregation and measurement scale on ranking a compromise alternative in ahp," *Journal of the Operational Research Society*, vol. 62, no. 4, pp. 700–710, 2011.
- [55] T. Yan, Y. Yang, and J. Xu, "Sparse paired comparisons in the bradley-terry model," *Statistica Sinica*, vol. 22, pp. 1305–1318, 2012.
- [56] Y. Zhang, L. Wang, Y. Chen, J. Xia, X. Li, and W. Lei, "P-31: Theory and application of paired comparison methods in display and lighting preference study," *SID Symposium Digest of Technical Papers*, vol. 43, no. 1, pp. 1174–1177, 2012.